A PORE-LEVEL APPROACH TO PETROPHYSICAL INTERPRETATION OF WELL LOGGING MEASUREMENTS

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ABSTRACT

An accurate description of water- or oil-bearing reservoirs and the assessment of reserves strongly depend on a robust determination of their petrophysical parameters, e.g., porosity, permeability and fluid distribution, reflecting fluid type, content, and mobility. Downhole measurements provide means to formation evaluation; however, they do not directly provide the petrophysical properties of interest. To interpret well logging data, a range of empirical models are usually employed. These empirical relationships, however, lack scientific basis and usually represent generalizations of the observed trends. To provide a link between a detailed description of the physical processes occurring at the pore scale and the macroscopic properties of sedimentary rocks, a pore-level approach to petrophysical interpretation of logging measurements is suggested in this work.

Powerful means to create such a link is to develop quantitative relationships between the petrophysical properties and the geologic processes involved in forming the rocks. Here we describe the use of simple but physically representative models of the results of several rock-forming processes, e.g., sedimentation and cementation. The key feature of these models is that they are geometrically determinate or precisely defined based on knowing the location of every grain comprising the model rock and hence the morphology of the pore space at the grain scale. We outline a method for computing formation permeability using the proposed rock models. Unlike many approaches to pore-level modeling, our approach introduces no adjustable parameters and thus can be used to produce quantitative, *a priori* predictions of the rock macroscopic behavior. NMR (Nuclear Magnetic Resonance) log contains information about porosity and grain size, allowing for an accurate petrophysical interpretation by means of the pore-level approach presented in this work.

The proposed methodology is applied to the field data and the corresponding interpretation results are included in this paper.

1. INTRODUCTION

Macroscopic formation properties (such as absolute and relative permeabilities, capillary pressure curves, formation resistivity factor) are fundamental to formation evaluation. In this work we consider the approach for *a priori* prediction of formation permeability from downhole NMR log measurements. Some formation properties are easily obtained from logging data, for example, porosity, bulk density, NMR T_1 and T_2 relaxation spectra, and compressional and shear wave velocities. Other petrophysical properties that are of importance to reservoir evaluation and development are difficult if not impossible to measure directly. These properties include grain size distribution, absolute and relative permeabilities,

capillary pressure curves, and formation resistivity factor and resistivity index. These are usually derived from empirical correlations with measured properties. The methodology presented here, on the other hand, is based on modeling of physical processes at grain scale, thus relating petrophysical properties of interest with measured data and providing a link between microscopic rock structure and its macroscopic parameters.

The idea is to conduct a theoretical investigation in a simple but physically representative model porous medium (Mason, 1971; Bryant and Blunt, 1992; Bryant *et al*, 1993; Mason and Mellor, 1995; Bryant and Pallatt, 1996; Bryant and Johnson, 2003; Gladkikh and Bryant, 2005; Gladkikh, 2005). Our approach is based on this previous research. The model is a numerically generated random close packing of equal spheres. The grain space and the void space in the packing are completely defined, thereby overcoming a long-standing difficulty for theoretical approaches. The goal of presented work is to utilize the developed pore-scale approaches for the successful routine petrophysical interpretation of downhole logging measurements. This particular problem, to our knowledge, has never been considered before.

2. PHYSICALLY REPRESENTATIVE MODEL POROUS MEDIA

We create random dense packing of equal spheres numerically. The collective rearrangement algorithm with periodic boundary conditions, based on (Clarke and Wiley, 1987), was implemented to pack spheres of equal size into the unit cube. Cylindrical core with length equal to diameter was then cut out of this unit cube. There are about 5,000 grains in this model core, and its porosity is about 36.8%, which corresponds to porosity of unconsolidated sands. Number of grains and geometrical features of the model core were chosen as a result of series of numerical simulations. These numbers should be large enough in order to make fair comparison with experimental core data, and at the same time small enough to provide fast numerical computations. The cylindrical core used in numerical simulations is shown on Fig. 1.
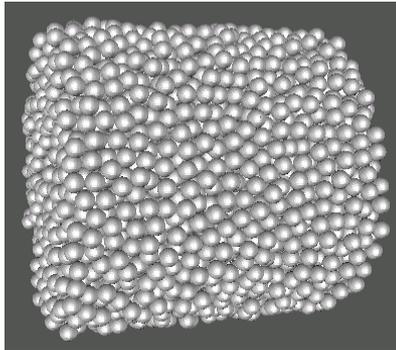

FIGURE 1. Numerically generated random dense packing of equal spheres. Cylindrical core, used in simulations. Number of grains is about 5,000; porosity is 36.8%.

In order to model fluid flow in the packing, we subdivide pore-space into a network of pore bodies and throats using *Delaunay tessellation* of sphere centers (Mason, 1971). We implement an algorithm for the Delaunay tessellation following (Thompson, 2002). The resulting network has "sites" (pore bodies), which correspond to the internal regions of tetrahedral Delaunay cells and "bonds" (pore throats), which correspond to the faces of those cells (Bryant *et al*, 1993). All geometric features of these pore bodies and throats (such as their volume, surface area, etc) follow directly from the known coordinates of sphere centers

(Gladkikh, 2005). In this work total number of 5,000 grains yields a network with about 25,000 pores and 52,000 pore throats.

The results of certain diagenetic processes can also be modeled in the packing, which allows creating simple models of sedimentary rocks (Bryant *et al*, 1993). In this work we consider the case of *isopachous* (e.g. quartz overgrowths) cement. It is also possible to model *pore-filling* cement (e.g. calcite) (Gladkikh, 2005). Isopachous cementation can be represented easily by increase of radii of all spheres without changing any of the spatial coordinates of grain centers (Bryant *et al*, 1993).

The model of fluid flow through porous media is based on the methodology suggested in (Bryant and Blunt, 1992; Bryant *et al*, 1993). The idea is to compute fluid flow in the network extracted from the packing using modified Delaunay tessellation (see above). The detailed description of the methodology, discussion of its' accuracy, and comparison with experimental data can be found, for example, in (Bryant and Blunt, 1992; Bryant *et al*, 1993; Gladkikh, 2005).

3. MODEL OF NMR RESPONSE

Nuclear magnetic resonance log is probably the only downhole measurement that contains information that can be related to grain size. Without such information it is impossible to make accurate predictions of some important properties of the rock, such as absolute permeability and capillary pressure curves. Numerical simulations are by their nature *dimensionless*, and therefore their results must be scaled appropriately to obtain desired *dimensional* properties. NMR logging data therefore provide an opportunity to infer grain size for the successful scaling of dimensionless predictions. NMR techniques are usually employed in petroleum industry to either predict permeability or for fluid typing. The former application uses the surface relaxation mechanism to relate measured relaxation spectra with surface-to-volume ratios of the pores and then employ latter to estimate permeability. The common approach is based on Brownstein and Tarr (1979) model. They have computed an exact solution of the diffusion equation for total magnetization with surface-like sinks in an *isolated spherical pore*. This solution is a sum of decreasing exponential functions. Moreover, they have shown, that in the *fast diffusion limit*, given by the expression

$$\frac{\rho r}{D} << 1, \tag{1}$$

where ρ is surface relaxivity, r is the radius of spherical pore, and D is water diffusivity, the lowest relaxation mode has much larger amplitude than other modes, and in this case total magnetization decays in time as a single exponential function:

$$M(t) = M_0 \exp\left(\frac{-t}{T_2}\right), \tag{2}$$

where M_0 is the initial magnetization and the transverse relaxation time T_2 is given by

$$\frac{1}{T_2} = \rho \frac{S}{V}, \tag{3}$$

where S/V is the surface-to-volume ratio of the pore. The model, described by equations (1–3), is applied widely in petroleum industry now, often disregarding assumptions that were used in its derivation. The real pore space, however, does not consist of isolated spherical pores, but is rather a complicated network-like structure of converging-diverging sections.

Non-sphericity of pores questions the derivation of Eqs. (1–3). Higher relaxation modes of the single pore may give significant contribution in the case of real pore space, when fast diffusion limit (1) is not satisfied. Presence of connections between pores makes possible pore-to-pore coupling.
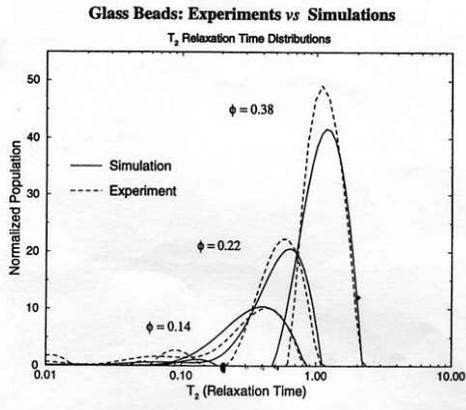

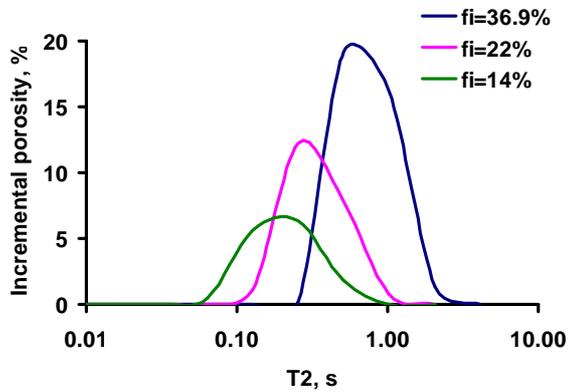FIGURE 2. Experimental NMR T_2 distribution for fused glass bead packs (Straley and Schwartz, 1996).

FIGURE 3. Predicted NMR T_2 distribution for numerical packing with isopachous cement.

There exist numerical models that utilize random-walk Monte-Carlo simulations to simulate relaxation process (Straley and Schwartz, 1996; Toumelin *et al*, 2003). This approach automatically resolves all complications in NMR interpretation, mentioned above. Unfortunately, high computation costs preclude its application to log interpretations. Moreover, grain size is usually unknown *a priori*, and one of the problems is to derive it from the measured relaxation spectra. In this case much faster algorithms are needed.

Here we suggest the following approach. The model is based on predicting NMR transverse relaxation spectrum in a random dense packing of spherical particles of uniform size (Fig. 1). This uniform size is an approximation of various grain size distributions that occur in real sediments; in case of such distributions mean value of grain size can be used in the model. Modified Delaunay tessellation subdivides pore space of the packing into tetrahedral pores. Surface-to-volume ratio is easily computed for each pore. If the values of grain size and surface relaxivity are specified, the application of Eq. (3) immediately yields T_2 spectrum for the packing fully saturated with water. Figs. 2 and 3 depict a comparison between experimental T_2 spectrum (unconsolidated and fused glass beads, grain diameter is 100 μm (Straley and Schwartz, 1996), Fig. 2) and predictions for the numerical packing with isopachous cement (Fig. 3). Predictions were made using values of surface relaxivity, reported by Straley and Schwartz (1996). The agreement between measured and simulated spectra is very good.

4. APPLICATION TO LOG INTERPRETATION

One of the most important applications of NMR logging is permeability estimation. The most widespread permeability prediction model used with NMR data is the so-called Timur-Coates equation (see, for example, Coates et al, 1991), which estimates the permeability using

subdivision of the relaxation spectrum into the contributions from "movable" (Bulk Volume Movable – BVM) and "capillary bound" (Bulk Volume Irreducible - BVI) fluids:

$$K_C = \left(\frac{\phi}{C}\right)^4 \left(\frac{BVM}{BVI}\right)^2. \tag{4}$$

Here C is empirical constant and BVM+BVI $= \phi$. For a given T_2 distribution the values of BVM and BVI are defined by some threshold value of transverse relaxation time $T_{2cutoff}$. This threshold is also purely empirical; the value of 33 ms is commonly used for sandstones. The basis of Eq. (4) is, in fact, Kozeny – Carman type (see, for example, Carman, 1956) relationship for permeability derived from the bundle of capillary tubes model. In order to use Eq. (4) one must first determine two empirical constants ($T_{2cutoff}$ and C), which questions practical applicability of the model.

In this work different approach is suggested: instead of attempting to derive an equation for permeability estimate from NMR data, we invert relaxation spectrum in order to infer *grain size* from it. We compute NMR response as described above. Then we simulate T_2 distribution numerically for a range of grain sizes. As an estimate for mean grain size, we choose the value that provides the closest fit to the measured data. As a criterion for fitting we use the minimization of net quadratic error for all bins in the relaxation spectrum. This value of grain size is used to scale computed dimensionless permeability to its dimensional value. Such a methodology allows inverting T_2 relaxation spectrum to compute absolute permeability of the formation, using an algorithm for modeling fluid flow, described above. It should be pointed out here, however, that this technique is based on Brownstein – Tarr model (Eqs. (1-3)) and therefore inhibits all the limitations of this model described above. It is a subject of future work to develop the technique further to account for non-spherical pores, pore-to-pore coupling, and relaxation regimes when fast diffusion limit (1) is not satisfied.

The application of the described technique is limited neither to the case when only one phase is present in the formation, nor to the specific geologic model (monominerallic grains, isopachous cement). Pore-filling cement can be taken into account as described in (Gladkikh, 2005). Further, if at the given depth two phases (water and oil) are present in the formation, the following procedure is used. First, we subdivide NMR T_2 relaxation spectrum into two different contributions (from water and oil correspondingly). This can be done, for example, using diffusivity contrast (Kleinberg and Vinegar, 1996). Having thus a signal only from the wetting phase (usually water) and knowing therefore its saturation, we simulate drainage (or imbibition, depending on the reservoir conditions), until this saturation is reached, using algorithms, described in (Bryant and Johnson, 2003; Gladkikh and Bryant, 2005; Gladkikh, 2005). Surface areas and volumes of different wetting phase configurations are computed directly from pore geometry (Gladkikh, 2005), thus contributing to NMR relaxation spectrum by means of Eq. (3). In the case of different mineralogy of grains (for example, in the presence of quartz and feldspar grains), Eq. (3) is modified as

$$\frac{1}{T_2} = \frac{1}{V} \sum_{Ngrains} \rho_i S_i, \tag{5}$$

where the sum is taken over all grains that form the pore, and ρ_i and S_i are corresponding values of surface relaxivity and surface area for each grain. Finally, it should be possible to extend the model for the presence of authigenic clays. It is a subject of future research.

Moreover, the methodology for inverting NMR T_2 relaxation spectrum for the mean grain size, presented here, can be combined with the previous research in pore-scale modeling to predict capillary pressure curves (Mason and Mellor, 1995; Bryant and Johnson, 2003; Gladkikh and Bryant, 2005; Gladkikh, 2005), relative permeabilities (Bryant and Blunt, 1992; Gladkikh, 2005), and electrical properties of the formation (Bryant and Pallatt, 1996, Gladkikh, 2005).

Fig. 4 presents the log of a well from Johnson City and its petrophysical interpretation. Johnson City Stribling #3 well was drilled using a 6 11/16'' bit size, through well-consolidated formations. At the zone object of this analysis the well traverses various clean to very shaly sands in a fresh water environment. The portion of the well shown on Fig. 4 consists primarily of clean quartzose and feldspathic sandstones. The well has been extensively cored during the drilling. Data obtained from the cores include porosity, grain density, and permeability. The core data were depth matched, interpolated to the level spacing of the logs (4 samples/feet), and filtered (using an 11 points weighted filter, the standard one used for 4s/ft logs) in order to provide a fair comparison with the log data (for the information on NMR logging tool principles, see, for example, (Edwards, 1997)). Since only water is present in the formation, single phase model described above is applicable here. Track 1 shows depth in feet. Track 4 shows NMR T_2 relaxation spectrum in ms. Track 2 presents porosity: total NMR porosity (MPHS, the integration of the complete T_2 distribution curve is assumed to represent the total porosity of the rock); NMR Clay Bound Water (MCBW, signal below 3 ms); NMR Bound Volume Irreducible (MBVI, signal below 33 ms), and NMR Effective Porosity (MPHE, total minus MCBW). Track 3 depicts permeability: core data (brown dots are actual core permeabilities and red curve is filtered core data); prediction using Timur-Coates Eq. (4) (blue curve), and prediction of the model described in this paper (green curve). Both Timur-Coates model and our model were calibrated to one point (depth 1236 ft). Core measurements at this depth provide porosity of 9.3% and permeability of 31 md (MPHS reads porosity of 8.5%). Parameter C of Eq. (4) was chosen so that permeability prediction matches core data. This value is $C = 6.5$ (the default value of C to use in Eq. (4) is usually equal to 10). MPHE was used for ϕ in (4), MBVI for BVI, and MBVM=MPHE-MBVI for BVM. In order to apply pore-scale model, described in this paper, it is necessary to specify the value of surface relaxivity of quartz (we assume monominerallic grain composition and apply Eq. (3)). This parameter, in contrast to purely empirical constant C of Eq. (4), has physical nature and the value from various laboratory measurements can be taken. Matching predicted and core permeability at the depth of 1236 ft yields the value of quartz surface relaxivity 30 μm/sec. This is in range of values, reported in the literature for sandstones (Roberts *et al*, 1995).

Comparison between two predictions and core permeability shown on Fig. 4 allows making several important observations. Both models are able to make successful predictions in a highly permeable zone, where NMR signal exhibits sharp single peak (1084-1094 ft, indicated by red box on Fig. 4). Eq. (4), however, being extremely sensitive to the value of BVI, fails when NMR log shows substantial signal at shorter times. See, for example, depths around 1164 ft (indicated by the blue box on Fig. 4), where core data show permeable formation and Timur-Coates model yields basically zero permeability. This happens because BVI is very large (almost all the signal), which is most probably due to the presence of weathered feldspars and iron oxides, absorbed on grain surfaces. These do not affect permeability much but influence NMR relaxation spectrum. Another problem of Eq. (4) is

evident when BVI appears to be unreasonably small (see the region around the depth 1202 ft, indicated by green box on Fig. 4; BVI here is around 1% of total rock volume and permeability computed by Eq. (4) is about 400 mD). In this case (which is in all probability simply an effect of large grain size) Eq.(4) overestimates permeability by more than an order of magnitude. Pore-scale model, on the other hand, being based on a simple, but reasonable geological and physical assumptions, is more consistent with core data. Moreover, since these assumptions are known, it is possible to identify the reasons for the failure of the model in the zones where it does not work. In such cases more geologic data are necessary in order to build more representative pore-scale model. On the other hand, empirical equations, like Eq. (4), do not provide any possibility for different physical interpretation, and one usually adjusts empirical coefficients (C and $T_{2cutoff}$ for the case of Eq. (4)) in the zones when this empirical equation fails.
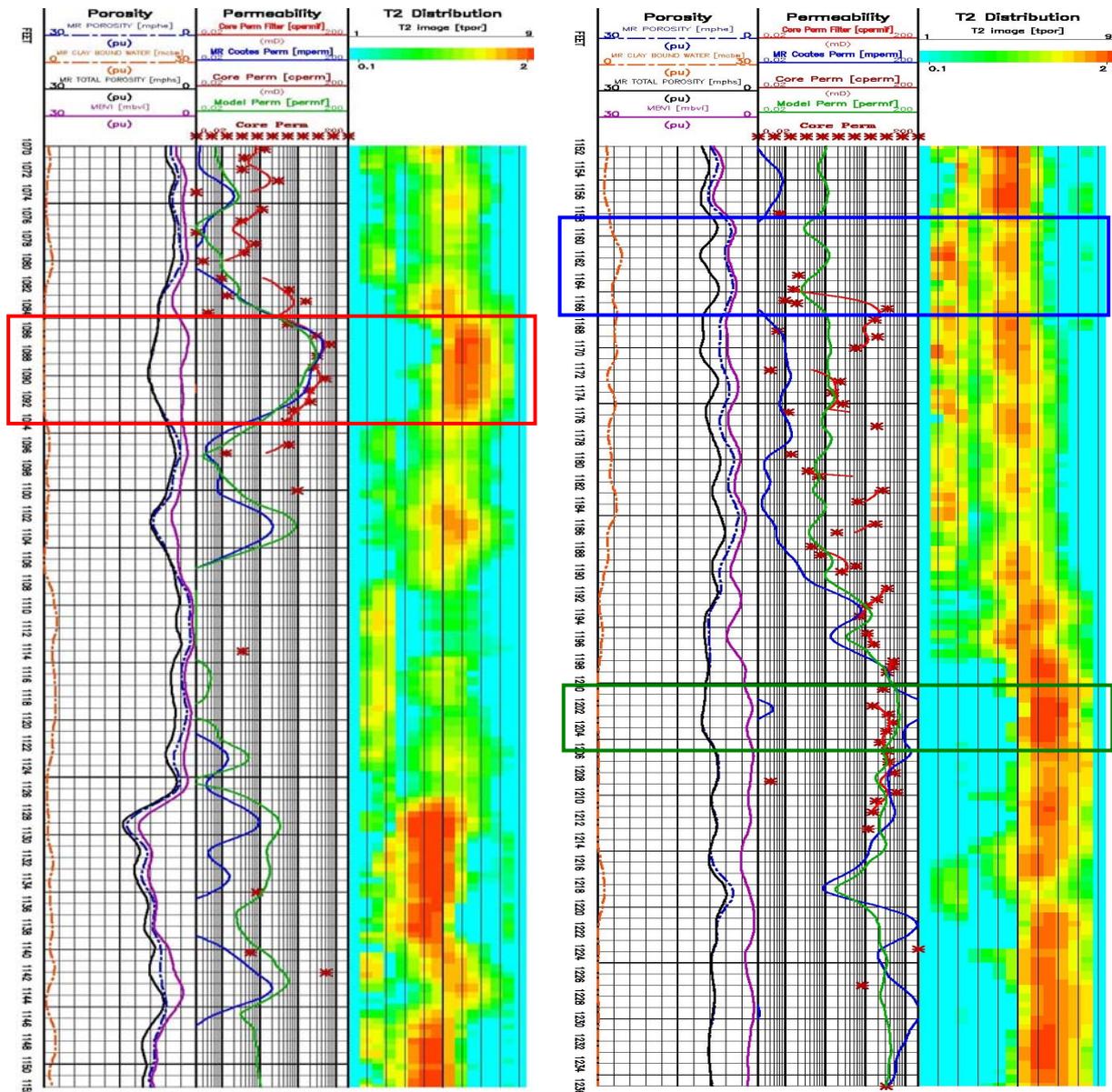

FIGURE 4. NMR log of the well from Johnson City and prediction of permeability

5. CONCLUSIONS

This work presents the approach for petrophysical interpretation (prediction of permeability) of downhole measurements using detailed geometric pore-scale description of physically representative model porous medium (numerical dense random packing of equal spheres). Porosity and mean value of grain size of the model rock are derived from log measurements data. The methodology was applied to the selected well and its' prediction of formation permeability were found consistent with existing core data.

REFERENCES

- Brownstein, K.R., and C.E. Tarr (1979), Importance of classical diffusion in NMR studies of water in biological cells, *Physical Review A 19*(6), 2446 – 2453.
- Bryant, S.L., and M. Blunt (1992), Prediction of relative permeability in simple porous media, *Phys Rev A, 46*, 2004-2011.
- Bryant, S.L., and A.S. Johnson (2003), Wetting phase connectivity and irreducible saturation in simple granular media, *J Coll Int Sci 263*(2), 572 – 579.
- Bryant, S.L., D.W. Mellor, and C.A. Cade (1993), Physically representative network models of transport in porous media *AIChE J 39*, 387-396.
- Bryant, S.L., and N. Pallatt (1996), Predicting formation factor and resistivity index in simple sandstones, *J Pet Sci Eng 15,* 169-179.
- Carman, P.C. (1956), Flow of gases through porous media, Butterworths.
- Clarke, A.S., and J.D. Wiley (1987), Numerical simulation of the dense random packing of a binary mixture of hard spheres: Amorphous metals, *Physical Review B 35* (14), 7350 – 7356.
- Coates, G.R., R.C.A. Peveraro, A. Hardwick, and D. Roberts (1991), The magnetic resonance imaging log characterized by comparison with petrophysical properties and laboratory core data. *SPE paper 22723*, proceedings of the 66th Annual Technical Conference and Exhibition, Formation Evaluation and Reservoir Geology, SPE, 627 – 635.
- Edwards, C.M. (1997), Effect of tool design and logging speed on T_2 NMR log data, *paper RR, 38th SPWLA Annual Logging Symposum Transactions*, Houston, TX, USA.
- Gladkikh, M. (2005), *A priori* prediction of macroscopic properties of sedimentary rocks containing two immiscible fluids. PhD Dissertation Thesis, University of Texas at Austin, Austin, TX, USA.
- Gladkikh, M., and S.L. Bryant (2005), Prediction of imbition in unconsolidated granular materials, *J Coll Int Sci 288*, 526 – 539.
- Kleinberg, R.L., and H.J. Vinegar (1996), NMR properties of reservoir fluids, *The Log Analyst, 37*(6), 20 – 32.
- Mason, G.J. (1971), A model of the pore space in a random packing of equal spheres, *J Coll Int Sci 35*, 279-287.
- Mason, G.J., and D.W. Mellor (1995), Simulation of drainage and imbition in a random packing of equal spheres, *J Coll Int Sci 176*, 214 – 225.
- Roberts, S.P., P.J. Macdonald, and T. Tritchard (1995), A bulk and spatially resolved NMR relaxation study of sandstone rock plugs, *J. Magn. Reson. A 116,* 189 – 195.
- Straley, C., and L.M. Schwartz (1996), Transverse relaxation in random bead packs: comparison of experimental data and numerical simulations, *Magnetic Resonance Imaging 14* (7/8), 999 – 1002.
- Toumelin, E., C. Torres-Verdin, S. Chen, and D.M. Fischer (2003), Reconciling NMR measurements and numerical simulations: assessment of temperature and diffusive coupling effects on two-phase carbonate samples, *Petrophysics 44* (2), 91 – 107.
- Thompson, K.E. (2002), Fast and robust Delaunay tessellation in periodic domains. *International Journal for Numerical Methods in Engineering*, 55, 1345 – 1366.